Desperate Times Call for Valuable Measures:
Impact of Macro Conditions on Value of Analyst Output in Finland

Antti Makkonen

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Abstract

This paper studies the implications of macroeconomic conditions on the price-impact following analyst output in Finland. In general, bad times make firm prospects more difficult to value, and thus investors should value analyst output more. Conversely, the same uncertainty makes analyzing firm prospects more difficult, and the output less reliable. I find weak evidence for analyst recommendation revisions having a larger stock-price impact in bad times. Equivalently, I find weak evidence for local analysts providing more valuable output and investors' reliance on analysts increasing in bad times. However, results with an alternative benchmark provide strong evidence for recommendation changes having a larger price-impact in bad times, consistent with analyst output being more valuable in bad times.

Keywords: Analyst; Sell-side; Recommendation; Price-impact; Event study

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Aalto University School of Business

Department of Finance

Thesis Instructor: Sean Shin

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1. Introduction

The value of sell-side research, its impact on stock-prices, and financial analysts' role as information intermediaries has been researched thoroughly (e.g., Womack (1996); Barber, Lehavy, Trueman (2007); Loh and Stulz (2011); Bradley, Clarke, Lee, Chayawat (2014)). A central shortcoming in the associated literature however is that the implications of macroeconomic conditions are mostly dismissed, although some studies on the implications of bad times have been conducted in the US (e.g., Kretzmann, Maaz, Pucker (2015); Loh and Stultz (2018)). The lack of research focus on the implications of bad times is unjustified in terms of macro uncertainty creating greater variation in firm outcomes (e.g., Bloom (2009)) and more ambiguity in firm value for investors (Zhang (2006)).

Bad times are also known to make it more difficult for analysts to assess implications of the underlying economic conditions, apparent in larger earnings forecast errors in bad times (e.g., Hope and Kang (2005)). Despite the pronounced implications of bad times to the information environment and analyst output, little research is conducted on the impact on value over various macroeconomic times and markets. Hence, the question remains whether increases in macroeconomic uncertainty increases the value of analyst output in Finland or not.

The purpose of this paper is to assess whether sell-side analyst output is more valuable in bad economic times in Finland. I contribute to the literature in three main ways. First, I study the value of analyst output in both good and bad times in Finland by incorporating the methodology of Loh and Stulz (2018). To assess value, I constitute a two-day event study on the price-impact following analyst recommendation changes. Next, I assess if local analysts provide more valuable output than foreign peers in bad times by comparing the same price-impact. As reference, Bae, Stulz, and Tan (2008) find that local analysts issue more precise earnings forecasts than foreign peers. Finally, I study if the perceived value-effect arises from investors' increased reliance on analyst output by examining if the price-impact is larger for harder-to-value stocks, following Loh and Stulz (2018).

I find weak evidence for sell-side analyst output being more valuable in bad macroeconomic times in Finland. Moreover, I find similarly weak evidence for local analysts issuing more valuable output and semi-strong evidence for the effect fluctuating in tandem with the geographical scope of bad times. Subsequently, I am not able to contribute differences in value to changes in investors' needs. However, I find strong evidence for analyst output being more valuable in bad times using the CAPM as a benchmark, consistent with the findings of Loh and Stulz (2018).

The remainder of the paper is structured as follows: Section 2 presents the existing literature on the value of sell-side analyst output and describes the hypotheses. Section 3 introduces the data sample and the methodologies used to test the hypotheses. Section 4 presents the results. Section 5 adds the CAPM and the Carhart Four-Factor Model as benchmarks and controls for analyst, recommendation, and firm characteristics. Section 6 concludes and presents recommendations for future research.

2. Literature Review and Hypotheses

2.1. Sources of Analyst Output Value

Studies on the value of sell-side research in bad times have been conducted in the US (e.g., Barber et al. (2001); Loh and Stultz (2018)). However, these papers focus on examining the effects in the US and it is unclear whether these effects apply in Finland as well. Finnish financial markets differ from the US in many characteristics, such as liquidity, role of financial markets in the overall economy, dependency on foreign trade, and share of institutional ownership (e.g., Nyberg, Vaihekoski (2014); Haaparanta et al. (2017); Puttonen (2004)). It is thus unclear whether the effects exist in Finland and to what extent.

Conversely, studies on the effects of analyst output have been conducted in Finland but none have covered the impact of macroeconomic conditions. If bad times such as recessions and crises increase macroeconomic uncertainty and it is the role of analysts to assess the implications of those times, analyst output should be more valuable. I study the value of analyst output over various bad times by incorporating multiple proxies for them. I use the same definitions of bad times as Loh and Stulz (2018) to study the effect in Finland vis-á-vis the findings from the US.

I focus on bad macroeconomic times instead of firm-specific bad times because they influence the broad economy and are exogenous to analysts. Analysts' ability to analyze firm's idiosyncratic risk has been researched thoroughly, and for instance Frankel and Weber (2006) show that analyst output is more valuable when firm-level uncertainty is higher. For the measure of value, I incorporate the view that if analyst output has an effect on stock-prices, it changes investors' priors and is therefore valuable to investors (Loh and Stulz (2018)).

My specific measure of the value of analyst output is a two-day Cumulative Abnormal Return (CAR), which captures the extent the new information in analyst output changes investors' priors during a two-day event window. I do not explore pre-event information leakage since I am not able to reliably isolate the pre-event price-drift on the output. I examine the effect following recommendation changes, divided into upgrades and downgrades, rather than recommendation or price levels because absolute levels of recommendations can be biased and therefore recommendation changes are more reliable at assessing analyst impact (e.g., Boni and Womack (2006)).

The extent new signals change investors' priors depend on the weight investors put on the new signal compared to their prior signal (Pástor and Veronesi (2009)). Thus, differences in the price-impact over varied macroeconomic times can arise from either more valuable analyst output or changes in how investors value the output. Throughout the paper, I assume that analysts do not change what they do per se in bad times. The implication for fixed analyst behavior is that analyst output is consistent with regards to all external factors at all times, and that the bad time-effect occurs because investors value analyst output differently.

It is plausible however that in bad times analysts change their behavior for example by changing how much they work, being differently motivated, using different skills or having conflicts of interest (Loh and Stulz (2018)). As an example of analyst output being more valuable, Michaely and Womack (1999) show that analysts face less pressure to produce optimistic research in bad times due to less investment banking business, which can bias the output. Kacperczyk, Veldkemp, and Van Niewerburgh (2013) find that fund managers do better in bad times, because they showcase better market-timing skills. Further, Glode (2011) presents that investors expect fund managers to fare better than the market more in bad times than good times. Hence, analysts might also be inclined to have skill in analyzing macroeconomic bad times just like fund managers.

Conversely, bad times can also affect analyst output negatively. For example, Betrand and Mullainathan (2001) show that analysts can use the higher underlying noise in bad times to hide their lack of effort. Also, lesser deal flow, lower valuation levels, and trading volume in bad times can shrink profits for financial institutions in general and therefore decrease analyst motivation. In addition to shrinking profits, bad times can cause conflicts of interests within financial institutions. For instance, Barber et al. (2007) show that analysts in institutions with investment banking business are more reluctant to downgrade stocks compared to peers in independent research firms.

Bad economic times can also affect how investors react to new information. All else equal, if bad times increase the noise in investors' priors more than in new analyst output, investors should value analyst output more (Loh and Stulz (2018)). The noise in analyst signals compared to investors' priors can decrease in two ways. Either analysts provide signals with less noise than in investors' priors or investors' other sources of information decrease, making analysts output relatively less noisy.

As evidence for higher reliance on analyst output, Kacperczyk and Seru (2007) find that investors with more private information rely less on analysts. Thus, if the underlying market uncertainty increases in bad times and investors' other signals become noisier, investors might have to rely more on analyst output. Also, there is evidence that investors react more to earnings news in bad times (Schmalz and Zhuk (2017)), and perhaps react more to all types of news in bad times. An alternative view by Hirshleifer, Lim, and Teoh (2009) suggests that in bad times more news hit the market, which distracts investors and leads to underreaction.

Although I use the price-impact followed by recommendation changes as the de-facto proxy for value, it is plausible that other, investor or market-related factors affect the price-impact, thus diluting the observable value of the output. Under the efficient-market hypothesis (EMH), new information gets reflected in asset prices immediately and correctly, yet due to market imperfections exogenous to analyst output this may not occur. For example, investment strategies, tax-policy on capital gains and losses, transaction costs as well as human psychology can alter the behavior of investors and the price-impact over economic cycles (Chang 2011)). Moreover, the observable stock-price impact is not the only manner in which analysts add value. Increasing the number of analysts and competition in the information market yields positive externalities other than the price-impact. More competition increases average forecast accuracy, alleviates information asymmetries among market participants, and enables more efficient information dissemination (Merkley, Michaely, Pacelli (2017)).

2.2. Hypotheses

Following the methodologies of Loh and Stulz (2018), I examine whether the state of the economy affects stock-price impacts following analyst recommendation revisions and explore a possible explanation for the results. First, I develop three hypotheses that examine whether analysts provide more valuable output in bad times, whether the location of the analyst, and the scope of the macroeconomic uncertainty affects the outcome. Next, I develop an additional hypothesis that examines why investors might value analyst output more in bad times.

H1: ***Bad times increase the value of analyst output***

The hypothesis assumes that analysts' relative ability to analyze the macroeconomic environment and its effects increases relative to investors' priors, which leads to an increased price-impact is bad times. Hope and Kang (2005) find analysts' earnings forecasts to be less accurate in bad times, which predicts analyst output to have a smaller stock-price impact in bad times. However, Loh, and Stultz (2018) find that in bad times earnings forecasts are relatively more accurate controlling for the underlying volatility and that analyst revisions have a larger price-impact controlling for analyst, recommendation, and firm characteristics. Effectively, this is a joint-hypothesis of comparing analyst output value, investors' dependency on the output, and the efficiency of the underlying institutions that constitute the price-discovery process (Hasbrouck (1995)).

H2: ***Local analysts are better at analyzing the implications of bad times on local firms***

The hypothesis assumes that local analysts have an absolute advantage in covering Finnish companies compared to foreign peers in bad times. Bae, Stultz, and Tan (2007) find that local analysts' earnings forecasts are more precise, which arises from their proximity to the covered firms and not due to analyst differences. However, the study does not examine how macroeconomic conditions affect the outcomes and whether changes in the scope of the macroeconomic conditions impact the result. Also, it is unclear whether local analysts have a relative advantage in covering Finnish companies, because local analysts have lower information costs yet might suffer from underwriter affiliation or other biases (e.g., Michaely & Womack, (1999)). This hypothesis tests both the value of the output as well as investors' behavioral attitudes towards analysts from different locations.

H3: ***Value of analyst output increases as the geographical scope of bad times narrows***

This hypothesis assumes that the value of both all analyst as well as local analyst output fluctuates in tandem with the geographical scope of bad times. More specifically, both effects are expected to shrink going from Finnish to European bad times. The implicit assumption is that economies, markets, and companies are interconnected yet different, and that analysts are the better at analyzing the implications the narrower the scope of the macroeconomic conditions. Past research finds both causal linkages and asymmetrical outcomes between countries and companies. For example, Chinn and Forbes (2004) find some evidence of cross-country factors that determine individual country's stock market returns. Finland's dependency on trade and relative proximity to Europe's largest economies suggest a strong linkage between financial markets and thus it is unclear whether the effects exist.

H4: ***Investors' reliance on analyst output increases in bad times***

The hypothesis explores one explanation why investors might value analyst output differently in bad times. The assumption is that investors' relative need for analyst information increases in bad times and thus they value analyst output more in bad times. For example, Kacperczyk and Seru (2007) find that investors with more private information rely less on analyst output and vice versa. I test this by comparing the price-impact for non-opaque and opaque stocks, for which there is less information available and for which investors require more information to assess at all times. I define stocks with low analyst coverage and small size as opaque. The hypothesis implicitly considers whether increased macro uncertainty raises the demand for information of the implications of bad times and if analysts are able to answer to the demand. An increased difference in the price-impact for opaque versus non-opaque stocks indicates that investors' reliance on analyst output increases in bad times.

3. Data and Methodology

3.1. Bad Times Measures

I employ four proxies for bad macroeconomic times in 2006 to 2015. The proxies capture bad times in the financial markets, the real economy, and uncertainty regarding the present and future of the economy. I include macro bad times in the scope of Europe as well as Finland specifically. Timewise, political uncertainty is an ex-ante and recessions an ex-post proxy for effects in the financial markets and allows examination of changes in investors' needs at different phases of economic cycles. As the first proxy I use the financial crisis; *Credit Crisis* equals the period from November 2007 to March 2009. The second proxy, *Recession Europe,* equals NBER-defined recessions in Europe[1], specifically the periods from March 2008 to June 2009 and June 2011 to March 2013.

The third proxy, *Recession Finland,* uses the same definition in Finland[2], which equals January 2008 to June 2009 and December 2011 to March 2015. The fourth proxy is the Baker, Bloom, and Davis policy uncertainty index in Europe. *High Uncertainty* equals times when the Europe historical index[3] is in the top tercile of values between 2006 and 2015. Separately, *Credit Crisis, Recession Europe, Recession Finland* and *High Uncertainty* classify *14%*, *32%, 48%,* and *32%* of the sample months as bad times, respectively. I define good times as non-bad times, following Loh and Stulz (2018).

[1, 2] NBER-defined recessions are from the website: https://www.nber.org/
[3] Data on the Economic Policy Uncertainty Monthly Index are from the website: http://www.policyuncertainty.com/

3.2. Stock Recommendations and Returns

I obtain data from Thomson Financial's I/B/E/S International Detail file. Specifically, individual analyst recommendations for Nasdaq OMX Helsinki (OMXH) companies from 2006 to 2015. Following Ljungqvist, Malloy, and Marston (2009), I define upgrades and downgrades by comparing an analyst's current rating to a prior rating by the same analyst. Although I/B/E/S reports ratings on a scale of 1 (strong buy) to 5 (strong sell), I focus on recommendation revisions and not levels since prior research finds recommendation levels to be biased and less informative than rating changes (e.g., Boni and Womack (2006)).

Incorporating the methodology of Ljungqvist et al. (2009), I consider prior ratings to be outstanding if they have not been stopped according to the I/B/E/S Stopped file and are issued less than one year before the current recommendation. If a recommendation is issued after trading hours or on a non-trading day, I move the recommendation date as the next trading day. I exclude anonymous analysts and recommendations with no outstanding prior rating from the same analyst, i.e. analyst initations and reinitations.

I remove revisions that occur on firm-news days because I do not want the revisions to merely repeat the information of the firm-news releases. Although Loh and Stultz (2018) find that analysts piggyback less on firm-news days in bad economic times, I want to examine specifically the value of new information in analyst output. I define firm-news days as firms' earnings announcement days. In addition, I remove recommendation changes which have occurred on days where multiple analysts have issued a recommendation for the same firm as in Loh and Stulz (2011), to remove the piggyback effect among analysts.

Loh and Stulz (2018) note the concern that applying these filters to remove the piggyback effect can dismiss a larger amount of weaker-quality recommendations in bad times and thus give an upwardly biased sample on the value of the recommendations. However, as previously noted, analysts piggyback less in bad times. I retrieve return data of daily stock returns including net dividends of Nasdaq OMX Helsinki companies from January 2006 to December 2015 from Thomson Reuters Datastream. I neglect companies with little or no analyst coverage, i.e. if there are no valid recommendation changes for the company during the sample period.

3.3. Descriptive Statistics

Table 1 presents annual figures of analyst recommendations for Nasdaq OMX Helsinki companies from 2006 to 2015. In total, the sample consists of 13123 recommendations and 7782 recommendation changes. On average, 1312 recommendations are issued annually, and recommendation changes are distributed evenly between recommendation upgrades and downgrades. Further, local analyst recommendation changes comprise 72% of the total annual recommendation changes on average.

Note the decreasing trend in the share of foreign analyst recommendations and total recommendations after the Financial Crisis in 2008. Local and foreign analyst recommendation changes are distributed similarly to upgrades and downgrades. Notice I do not consider absolute recommendation levels since absolute levels of recommendations can be biased and therefore recommendation changes are more reliable at assessing analyst impact (e.g., Boni and Womack (2006)). Assessing differences in the overall outlook on the stock-market for local and foreign analysts is beyond the scope of this paper.

Table 1

Descriptive Statistics on Analyst Recommendations from I/B/E/S International file, 2006 - 2015

Table 1 reports annual observations of recommendations, divided into *Upgrades* and *Downgrades*, and their individual share of recommendation changes. A recommendation change is defined as the analyst's current rating minus their prior outstanding rating (initations and reinitations are excluded); changes made on earnings announcement days, and changes on multiple-recommendation days are excluded. Upgrades and downgrades are further divided by their issuer institution's origin into *Local Analyst Recs* and *Foreign Analyst Recs*. *Total Recs* includes all recommendations issued during the period. *Avg.* presents simple arithmetic means for all columns.

	Upgrades		*Downgrades*		*Local Analyst Recs*				*Foreign Analyst Recs*				*Total Recs*
Year	Obs	of All	Obs	of All	Up	Down	Total	of All	Up	Down	Total	of All	
2006	256	51%	245	49%	165	160	325	65%	91	85	176	35%	1317
2007	454	51%	430	49%	297	271	568	64%	157	159	316	36%	1526
2008	380	44%	483	56%	259	304	563	65%	121	179	300	35%	1503
2009	428	51%	411	49%	307	290	597	71%	121	121	242	29%	1322
2010	410	51%	398	49%	313	313	626	77%	97	85	182	23%	1376
2011	487	52%	448	48%	356	339	695	74%	131	109	240	26%	1704
2012	413	47%	458	53%	317	352	669	77%	96	106	202	23%	1234
2013	333	45%	401	55%	271	312	583	79%	62	89	151	21%	1111
2014	358	55%	289	45%	278	223	501	77%	80	66	146	23%	1006
2015	337	48%	363	52%	241	249	490	70%	96	114	210	30%	1024
Avg.	386	50%	393	50%	280	281	562	72%	105	111	217	28%	1312

Table 2

Descriptive Statistics on Analyst Recommendation Revisions from I/B/E/S International file, 2006 - 2015

Table 2 reports the two-day C*AR (*in percentage*)*, which is the average day [0,1] cumulative abnormal return following a recommendation change. A recommendation change is defined as the analyst's current rating minus their prior outstanding rating (initations and reinitations are excluded); changes made on company earnings announcement days, and changes on multiple-recommendation days are excluded. The benchmark return for the CAR is the return from a 30-day trailing characteristics-matched DGTW portfolio in Europe. Bad times measures are as follows. *Credit Crisis*: November 2007 to March 2009 (The Financial Crisis). *Recession EU*: March 2008 to June 2009, June 2011 to March 2013 (NBER-defined recessions in Europe). *Recession Fin*: January 2008 to June 2009, December 2011 to March 2015 (NBER-defined recessions in Finland). *High Uncertainty* represents the highest tercile (over the period January 2006 to December 2015) of the Baker, Bloom, and Davis policy uncertainty index in Europe. *Good Times* are non-bad times. *LFR* is the analyst's leader-follower ratio (calculated by dividing the time from the previous recommendation with the time to the next recommendation by another analyst). *# Analysts* is the number of analysts covering the firm*, Size* is the firm's market capitalization in thousands of euros and *MB* is the market-to-book ratio in the previous year from the recommendation.

	Credit Crisis			*Recession EU*			*Recession Fin*			*High Uncertainty*			*Good Times*		
Variable	Mean	Stdev	Obs	Mean	Stdev	Obs	Mean	Stdev	Obs	Mean	Stdev	Obs	Mean	Stdev	Obs
							Downgrade Sample								
CAR	-0.56	0.06	1152	-0.50	0.05	3887	-0.38	0.05	5227	-0.17	0.05	3714	-0.22	0.03	2554
LFR	4.0	10	1152	4.2	13	3887	4.9	14	5227	4.9	13	3714	4.1	11	2554
# Analysts	34	27	1152	34	27	3887	34	27	5227	35	27	3714	40	25	2554
Size	2885	4721	1152	2685	4664	3887	2798	5527	5227	3015	5810	3714	3030	5002	2554
MB	2.4	1.6	1152	2.2	1.6	3887	2.5	16.9	5227	2.2	1.7	3714	2.8	2.5	2554
							Upgrade Sample								
CAR	0.72	0.06	1810	0.59	0.05	3893	0.54	0.05	5233	0.60	0.05	3717	0.56	0.04	4893
LFR	4.1	10	1810	4.6	11	3893	4.9	15	5233	4.9	14	3717	4.2	12	4893
# Analysts	34	27	1810	34	27	3893	34	27	5233	35	27	3717	42	26	4893
Size	2427	2	1810	2406	5650	3893	2837	5731	5233	2975	5810	3717	3033	6217	4893
MB	2.3	1.8	1810	2.1	1.6	3893	2.5	16.9	5233	2.3	1.9	3717	2.8	2.6	4893

Table 2 presents the mean, standard deviation and number of observations for the variables *CAR, LFR, # Analysts, Size* and *MB* in different economic times, divided into Upgrade and Downgrade Samples. *CAR* represents the average two-day cumulative abnormal return against a 30-day trailing characteristics-matched DGTW portfolio following a recommendation change. In both samples the sign of the average *CAR* follows the direction of the recommendation change, positive for upgrades and negative for downgrades. In both samples the largest average *CAR* occurs during the *Credit Crisis,* followed by *Recession EU* in downgrades*,* which implies that investors are less familiar with the implications of bad times at the European scope and therefore value analyst output more in those times.

In the Upgrade Sample the second largest effect occurs during *High Uncertainty,* which could be due to investors valuing and liking positive sings and not wanting to drop out during uncertain times. *LFR* is calculated by dividing the time from the previous recommendation with the time to the following recommendation. A ratio of over one represents a leader analyst since other analysts react quickly to their recommendations. The average *LFR* has slightly increased from the *Credit Crisis* in other bad times measures. *# Analysts* presents the number of analyst covering each firm, which is on average over five analysts larger per firm in good times, in line with findings of Merkley et al. (2017). *Size* and *MB* present the market capitalization in thousands of euros and the market-to-book-ratio for each firm. *MB*s and *Size*s are larger in good times due to higher valuation levels, as is expected.

3.4. Methods

To study if recommendation changes yield higher abnormal returns in bad times, I conduct an event-study by adopting a 30-day estimation period and a two-trading event window following Loh and Stulz (2018). Specifically, I compute a two-day Cumulative Average Abnormal Return (CAAR) from the recommendation date to the following trading day, as in during the [0,1] event window for both upgrades and downgrades. As the benchmark return, I use the return from a characteristics-matched DGTW portfolio (following Daniel et al. (1997)), formally stated as:

$$R_{i,t} - R_{ft} = \alpha + \beta_{i1} SMB_t + \beta_{i2} HML_t + \beta_{i3} MOM_t + \varepsilon_{i,t} \tag{1}$$

where $R_{i,t}$ - R_{ft} is the return on stock i over the risk-free rate R_{ft} during time t. *SMB* is the size-, *HML* is the value-, and *MOM* is the momentum-factor, all daily returns on the factor-portfolios in Europe[4] . β_{i1}, β_{i2}, and β_{i3} are stock i's coefficients to the factors from the preceding 30 days. α is the intercept of the model and $\varepsilon_{i,t}$ is the error term. Next, I calculate the Abnormal Return separately for upgrades and downgrades on a single trading day t within the event-window as the return on stock i less the return on a characteristics-matched DGTW portfolio:

$$AR_{i,t} = R_{i,t} - R_{ft} - \beta_{i1} SMB_t - \beta_{i2} HML_t - \beta_{i3} MOM_t \tag{2}$$

To calculate the Average Abnormal Return for all codirectional recommendation changes N on trading day t within the event-window:

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{i,t} \tag{3}$$

The Cumulative Average Abnormal Return over the event window [0,1] is the sum of all Average Abnormal Returns ranging from day 0 to day 1:

$$CAAR_{0,1} = \sum_{t=0}^{0,1} AAR_t \tag{4}$$

[4] Daily returns for SMB, HML, MOM factors in Europe are from the website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

To test the robustness of the results, I incorporate both the CAPM and the Carhart Four-Factor Model as benchmarks. To calculate the Cumulative Average Abnormal Return, I first calculate the Abnormal Returns with both models and continue as with the DGTW portfolio. Starting with the CAPM:

$$AR_{i,t} = R_{i,t} - R_{ft} - \beta_{i1} (R_{mt} - R_{ft}) \tag{5}$$

where β_{i1} is stock i's coefficient with the OMX Helsinki Index over the risk-free rate (R_{mt} - R_{ft}). Using the Four-Factor Model, developed by Carhart (1997) to calculate the Abnormal Return:

$$AR_{i,t} = R_{i,t} - R_{ft} - \beta_{i1} (R_{mt} - R_{ft}) - \beta_{i2} SMB_t - \beta_{i3} HML_t - \beta_{i4} MOM_t \tag{6}$$

4. Results

4.1. Price-Impact of Recommendation Changes

Table 3 presents the average two-day CAR in percentages divided by their time of occurrence into *Credit Crisis, High Uncertainty, Recession Europe,* and *Recession Finland*, and further into downgrades and upgrades. Statistical significance is reported and based on standard errors clustered by calendar day. Both downgrades and upgrades have a larger impact during bad times. However, the difference to the effect in good times is statistically significant at the 5% level only during the *Credit Crisis,* as the average two-day CAR for a recommendation downgrade is -0.727% versus -0.294% in good times. Also, downgrades during *Recession Europe* result in an average CAR of -0.512% versus -0.294%, indicating a statistically significant difference at the 10% level.

The average CAR in bad times compared good times being statistically insignificant indicates that analyst output is mostly not more valuable in bad times, although the effect is larger in bad times in all but downgrades during *High Uncertainty.* The average CAR for both upgrades and downgrades during good and bad times is mostly statistically significant at the 1% level, which indicates that analysts do have an impact on market prices in both good and bad times. The findings are in conflict with Loh and Stulz (2018), who report statistically significant differences between good and bad times in the US for all bad time measures and for upgrades and downgrades at the 1% level.

The difference can be caused by differences in the sample, markets, analysts and their output as well as investor behavior. Their sample starts over 10 years before the one I use and includes the crisis of October 1987 and Long-Term Capital Management (LTCM) crisis of 1998. However, insignificant results during recessions and high uncertainty, which I define by using the same criteria, indicate that the differences do not solely arise from time difference in the samples. Also, I replicate the methods as closely as possible. Therefore, the results suggest that the difference in the price-impact for various economic times in the US and Finland arise from difference in how investors value analyst output or in the quality of the output itself. Section 4.3. studies change in investors' reliance on analyst output. Another cause for the difference can be the benchmark and it being more accurate in Finland for the stocks the recommendation changes consider. Section 5.1. introduces additional benchmarks.

Table 3

Recommendation Change Impact in Bad Times

Table 3 reports the two-day CAR *(*in percentage*)*, which is the average day [0,1] cumulative abnormal return following a recommendation change. A recommendation change is defined as the analyst's current rating minus their prior outstanding rating (initations and reinitations are excluded); changes made on company earnings announcement days, and changes on multiple-recommendation days are excluded. The benchmark return for the CAR is the return from a 30-day trailing characteristics-matched DGTW portfolio in Europe. Bad times measures are as follows. *Credit Crisis*: November 2007 to March 2009 (The Financial Crisis). *Recession Europe*: March 2008 to June 2009, June 2011 to March 2013 (NBER-defined recessions in Europe). *Recession Finland*: January 2008 to June 2009, December 2011 to March 2015 (NBER-defined recessions in Finland). *High Uncertainty* represents the highest tercile (over the period January 2006 to December 2015) of the Baker, Bloom, and Davis (2018) policy uncertainty index in Europe. *Good Times* are non-bad times. T-statistics are in absolute levels and based on standard errors clustered by calendar day. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

			Two-Day CAR (%)		
Bad Times Measure	Rec-Change	Variable	Bad Times	Good Times	Difference
Credit Crisis	Downgrade	Percent	-0.727	-0.294	-0.433
		t-stat	(4.22)***	(2.55)**	(2.09)**
		Obs	576	1277	
	Upgrade	Percent	0.542	0.453	0.089
		t-stat	(2.84)***	(4.11)***	(0.40)
		Obs	469	1398	
High Uncertainty	Downgrade	Percent	-0.235	-0.294	0.059
		t-stat	(1.97)**	(2.55)**	(0.36)
		Obs	1196	1277	
	Upgrade	Percent	0.569	0.453	0.116
		t-stat	(4.63)***	(4.11)***	(0.70)
		Obs	1126	1398	
Recession Europe	Downgrade	Percent	-0.512	-0.294	-0.218
		t-stat	(4.51)***	(2.55)**	(1.35)
		Obs	1316	1277	
	Upgrade	Percent	0.592	0.453	0.139
		t-stat	(4.76)***	(4.11)***	(0.84)
		Obs	1097	1398	
Recession Finland	Downgrade	Percent	-0.407	-0.294	-0.113
		t-stat	(4.19)***	(2.55)**	(0.75)
		Obs	1807	1277	
	Upgrade	Percent	0.538	0.453	0.085
		t-stat	(5.15)***	(4.11)***	(0.56)
		Obs	1557	1398	

4.2. Local versus Foreign Analyst Comparison

Table 4

Local versus Foreign Analyst Recommendation Change Comparison

Table 4 reports the two-day CAR (in percentage), which is the average day [0,1] cumulative abnormal return following a recommendation change for *Local Analysts* and *Foreign Analysts*. A recommendation change is defined as the analyst's current rating minus their prior outstanding rating (initations and reinitations are excluded); changes made on company earnings announcement days, and changes on multiple-recommendation days are excluded. Recommendations are divided into local and foreign based on their issuer institution's origin. The benchmark return for the CAR is the return from a 30-day trailing characteristics-matched DGTW portfolio in Europe. Bad times measures are as follows. *Credit Crisis*: November 2007 to March 2009 (The Financial Crisis). *Recession EU*: March 2008 to June 2009, June 2011 to March 2013 (NBER-defined recessions in Europe). *Recession Fin*: January 2008 to June 2009, December 2011 to March 2015 (NBER-defined recessions in Finland). *High Uncertainty* represents the highest tercile (over the period January 2006 to December 2015) of the Baker, Bloom, and Davis (2018) policy uncertainty index in Europe. *Good Times* are non-bad times. T-statistics are in absolute levels and based on standard errors clustered by calendar day. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

			Two-Day CAR (%)		
Time Measure	Rec-Change	Variable	*Local Analyst*	*Foreign Analyst*	Difference
Credit Crisis	Downgrade	Percent	-0.763	-0.663	-0.100
		t-stat	(3.55)***	(2.30)**	(0.39)
		Obs	369	207	
	Upgrade	Percent	0.846	-0.038	0.883
		t-stat	(3.60)***	(0.12)	(2.20)**
		Obs	308	161	
High Uncertainty	Downgrade	Percent	-0.085	-0.662	0.576
		t-stat	(0.62)	(2.82)***	(2.92)***
		Obs	886	310	
	Upgrade	Percent	0.588	0.509	0.079
		t-stat	(4.16)***	(2.05)**	(0.28)
		Obs	849	277	
Recession Europe	Downgrade	Percent	-0.465	-0.630	0.164
		t-stat	(3.46)***	(2.95)***	(0.85)
		Obs	941	375	
	Upgrade	Percent	0.642	0.461	0.181
		t-stat	(4.39)***	(1.94)*	(0.65)
		Obs	796	301	
Recession Finland	Downgrade	Percent	-0.393	-0.442	0.049
		t-stat	(3.45)***	(2.39)**	(0.27)
		Obs	1308	499	
	Upgrade	Percent	0.650	0.204	0.445
		t-stat	(5.38)***	(0.98)	(1.84)*
		Obs	1167	390	
Good Time	Downgrade	Percent	0.004	-0.314	0.318
		t-stat	(0.03)	(1.55)	(1.60)
		Obs	864	413	
	Upgrade	Percent	0.161	0.468	-0.307
		t-stat	(1.22)	(2.36)**	(1.29)
		Obs	965	433	

Table 4 presents the average two-day CAR in percentages for both local and foreign analyst recommendation changes divided into *Credit Crisis, High Uncertainty, Recession Europe, Recession Finland,* and *Good Times*. Statistical significance is reported and based on standard errors clustered by calendar day. There is some evidence for local analysts being more informative in Finnish bad times and the difference evening out as the scope widens to European bad times. For the average CAR following upgrades, the difference between local and foreign analysts during *Recession Finland* is 0.445% and drops to 0.181% during *Recession Europe.* Upgrades issued by local analysts during *Credit Crisis* result in an average CAR of 0.846% compared to -0.038% for foreign analysts, resulting in a difference of 0.883%, which is statistically significant at the 5% level. Further, the results indicate that local analysts are more informative in upgrades and foreign peers in downgrades.

Note the difference is significant at the 1% level for downgrades during *High Uncertainty*, although it is foreign analyst output which has the larger price-impact by 0.576%. Contradictory to the results, Bae, Stulz, and Tan (2008) find significant local analyst advantage especially in countries where earnings are smoothed, firms disclose less information and idiosyncratic risk explains a small fraction of stock returns. Thus, the indifference in the price-impact for local and foreign analysts in bad times can arise from similar firm fixed-effects, for which Section 5.2. adds controls. In addition, investor and analyst differences discovered in Section 4.1. can dilute the location-induced effects.

4.3. Opaque versus Non-Opaque Stock Comparison

Table 5 presents the average two-day CAR in percentages for recommendation changes on opaque and non-opaque stocks divided into *Credit Crisis, High Uncertainty, Recession Europe, Recession Finland,* and *Good Times*. Statistical significance is reported and based on standard errors clustered by calendar day. I find weak evidence for the price-impact being larger on opaque stocks and thus investors' reliance on analyst output increasing in bad times. The difference in the average CAR for opaque stocks is insignificant for all time measures and recommendation changes.

Note the small amount of observations of recommendation changes on opaque stocks, which I define as stocks ranking in the bottom half in both number of analysts covering the stock and market capitalization. The cause of the low amount of observations is that large and active analyst institutions do not cover the smallest stocks, leading to less recommendations qualifying as changes. The small amount of observations leads to recommendation changes on those stocks having a statistically insignificant impact on the two-day CAR, despite significant price-impacts percentage-wise.

Table 5

Opaque versus Non-Opaque Stock Recommendation Change Comparison

Table 5 reports the two-day CAR (in percentage), which is the average day [0,1] cumulative abnormal return following a recommendation change for *Opaque* and *Non-Opaque* stocks. *Opaque* stocks are stocks listed on OMX Helsinki that rank in the bottom half in both number of analyst covering the stock and last year's market capitalization. A recommendation change is defined as the analyst's current rating minus their prior outstanding rating (initations and reinitations are excluded); changes made on company earnings announcement days, and changes on multiple-recommendation days are excluded. The benchmark return for the CAR is the return from a 30-day trailing characteristics-matched DGTW portfolio in Europe. Bad times measures are as follows. *Credit Crisis*: November 2007 to March 2009 (The Financial Crisis). *Recession Europe*: March 2008 to June 2009, June 2011 to March 2013 (NBER-defined recessions in Europe). *Recession Finland*: January 2008 to June 2009, December 2011 to March 2015 (NBER-defined recessions in Finland). *High Uncertainty* represents the highest tercile (over the period January 2006 to December 2015) of the Baker, Bloom, and Davis (2018) policy uncertainty index in Europe. *Good Times* are non-bad times. T-statistics are in absolute levels and based on standard errors clustered by calendar day. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

			Two-Day CAR (%)		
Time Measures	Rec-Change	Variable	*Opaque*	*Non-Opaque*	Difference
Crisis	Downgrade	Percent	0.432	-0.793	-1.224
		t-stat	(0.58)	(4.48)***	(1.40)
		Obs	31	545	
	Upgrade	Percent	0.697	0.537	0.160
		t-stat	(0.64)	(2.77)***	(0.13)
		Obs	15	454	
High Uncertainty	Downgrade	Percent	-0.471	-0.228	-0.244
		t-stat	(0.67)	(1.88)*	(0.29)
		Obs	35	1161	
	Upgrade	Percent	0.650	0.566	0.084
		t-stat	(0.97)	(4.53)***	(0.10)
		Obs	38	1088	
Recession Europe	Downgrade	Percent	-0.372	-0.518	0.145
		t-stat	(0.64)	(4.46)***	(0.20)
		Obs	51	1265	
	Upgrade	Percent	0.483	0.597	-0.115
		t-stat	(0.79)	(4.69)***	(0.15)
		Obs	46	1051	
Recession Finland	Downgrade	Percent	-0.349	-0.409	0.059
		t-stat	(0.69)	(4.13)***	(0.09)
		Obs	67	1740	
	Upgrade	Percent	0.263	0.549	-0.286
		t-stat	(0.48)	(5.15)***	(0.39)
		Obs	57	1500	
Good Time	Downgrade	Percent	0.004	-0.314	0.318
		t-stat	(0.01)	(2.63)***	(0.49)
		Obs	82	1195	
	Upgrade	Percent	0.161	0.468	-0.307
		t-stat	(0.33)	(4.14)***	(0.44)
		Obs	70	1328	

5. Robustness Tests

5.1. The CAPM and 4F Model as Benchmarks

Table 6

Recommendation Change Impact in Bad Times

Table 6 reports the two-day CAR *(*in percentage*)*, which is the average day [0,1] cumulative abnormal return following a recommendation change. A recommendation change is defined as the analyst's current rating minus their prior outstanding rating (initations and reinitations are excluded); changes made on company earnings announcement days, and changes on multiple-recommendation days are excluded. Bad times measures are as follows. *Credit Crisis*: November 2007 to March 2009 (The Financial Crisis). *Recession EU*: March 2008 to June 2009, June 2011 to March 2013 (NBER-defined recessions in Europe). *Recession Fin*: January 2008 to June 2009, December 2011 to March 2015 (NBER-defined recessions in Finland). *High Uncertainty* represents the highest tercile (over the period January 2006 to December 2015) of the Baker, Bloom, and Davis (2018) policy uncertainty index in Europe. *Good Times* are non-bad times. In Panel A the benchmark return is a 30-day trailing beta-adjusted return of OMX Helsinki Total Return Index, which includes net dividends. In Panel B the benchmark return is from a 30-day trailing characteristics-matched Carhart Four-Factor Model. T-statistics are in absolute levels and based on standard errors clustered by calendar day. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

Panel A: CAPM Benchmark

Bad Times Measure	Rec-Change	Variable	Two-Day CAR (%) Bad Times	Good Times	Difference
Credit Crisis	Downgrade	Percent	-0.385	1.018	-1.403
		t-stat	(2.45)**	(9.65)***	(7.40)***
		Obs	576	1277	
	Upgrade	Percent	0.767	1.686	-0.919
		t-stat	(4.40)***	(16.73)***	(4.56)***
		Obs	469	1398	
High Uncertainty	Downgrade	Percent	-0.340	1.018	-1.358
		t-stat	(3.12)***	(9.65)***	(8.95)***
		Obs	1196	1277	
	Upgrade	Percent	0.471	1.686	-1.215
		t-stat	(4.20)***	(16.73)***	(8.05)***
		Obs	1126	1398	
Recession Europe	Downgrade	Percent	-0.413	1.018	-1.431
		t-stat	(3.97)***	(9.65)***	(9.66)***
		Obs	1316	1277	
	Upgrade	Percent	0.574	1.686	-1.112
		t-stat	(5.04)***	(16.73)***	(7.31)***
		Obs	1097	1398	
Recession Finland	Downgrade	Percent	-0.301	1.018	-1.319
		t-stat	(3.40)***	(9.65)***	(9.57)***
		Obs	1807	1277	
	Upgrade	Percent	0.612	1.686	-1.074
		t-stat	(6.41)***	(16.73)***	(7.73)***
		Obs	1557	1398	

Panel B: 4F Model Benchmark

Bad Times Measure	Rec-Change	Variable	Two-Day CAR (%) Bad Times	Good Times	Difference
Credit Crisis	Downgrade	Percent	-0.564	-0.220	-0.344
		t-stat	(3.06)***	(1.78)*	(1.55)
		Obs	576	1277	
	Upgrade	Percent	0.716	0.558	0.158
		t-stat	(3.51)***	(4.73)***	(0.67)
		Obs	469	1398	
High Uncertainty	Downgrade	Percent	-0.169	-0.220	0.051
		t-stat	(1.33)	(1.78) *	(0.29)
		Obs	1196	1277	
	Upgrade	Percent	0.599	0.558	0.041
		t-stat	(4.56)***	(4.73)***	(0.23)
		Obs	1126	1398	
Recession Europe	Downgrade	Percent	-0.505	-0.220	-0.285
		t-stat	(4.15)***	(1.78)*	(1.65)*
		Obs	1316	1277	
	Upgrade	Percent	0.586	0.558	0.028
		t-stat	(4.40)***	(4.73)***	(0.16)
		Obs	1097	1398	
Recession Finland	Downgrade	Percent	-0.389	-0.220	-0.169
		t-stat	(3.75)***	(1.78)*	(1.05)
		Obs	1807	1277	
	Upgrade	Percent	0.542	0.558	-0.016
		t-stat	(4.85)***	(4.73)***	(0.10)
		Obs	1557	1398	

Table 6 presents the average two-day CAR in percentages for recommendation changes divided into *Credit Crisis, High Uncertainty, Recession Europe,* and *Recession Finland.* Statistical significance is reported and based on standard errors clustered by calendar day. Panel A presents the results with the CAPM and Panel B with the Carhart Four-Factor Model as benchmarks. I find strong evidence for analyst output being more valuable in bad times using the CAPM model, consistent with the results of Loh and Stulz (2018). The results are statistically significant at the 1% level for all bad times and both upgrades and downgrades. Note the effect is lesser in bad times for both recommendation types.

The results from using the Carhart Four-Factor Model are similar to the results using the DGTW portfolio as a benchmark, presented in Section 4.1. I find weak evidence for additional value in bad times, as only downgrades during *Recession Europe* yield a statistically significant difference at the 10% level. The varied results for different models suggest that the difference between the US and Finland could be explained by difference in the markets and models' varying ability to describe them.

5.2. Effects of Analyst, Recommendation and Firm Characteristics

Table 7

Panel Regression of Recommendation Change CARs in Bad Times

Table 7 reports the effect of bad times on recommendation two-day CARs (in percentage), which is the average day [0,1] cumulative abnormal return following a recommendation change controlling for firm, analyst, and recommendation characteristics. A recommendation change is defined as the analyst's current rating minus their prior outstanding rating (initations and reinitations are excluded); changes made on company earnings announcement days, and changes on multiple-recommendation days are excluded. The benchmark return for the CAR is the return from a 30-day trailing characteristics-matched DGTW portfolio in Europe. Control variables are as follows. LFR is the analyst's prior-year leader-follower ratio, # Analysts is the number of analysts covering the firm, Size is the firm's market capitalization in the prior year, BM is the book-to-market ratio. Bad times measures are as follows. Credit Crisis: November 2007 to March 2009 (The Financial Crisis). Recession Europe: March 2008 to June 2009, June 2011 to March 2013 (NBER-defined recessions in Europe). Recession Finland: January 2008 to June 2009, December 2011 to March 2015 (NBER-defined recessions in Finland). High Uncertainty represents the highest tercile (over the period January 2006 to December 2015) of the Baker, Bloom, and Davis (2018) policy uncertainty index in Europe. Good Times are non-bad times. Panel A presents the results with the CAR of Downgrades and Panel B the CAR of Upgrades as the dependent variables. T-statistics are in absolute levels and based on standard errors clustered by calendar day. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Dependent Variable: CAR of Downgrades

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit Crisis	-0.433	-1.006						
	(2.09)**	(5.70)***						
High Uncertainty			0.059	-8.143				
			(0.36)	(0.58)				
Recession Europe					-0.218	-7.259		
					(1.35)	(1.39)		
Recession Finland							-0.113	-5.627
							(0.75)	(4.25)***
LFR		-7.583		2.214		-4.213		-2.793
		(0.13)		(1.55)		(0.07)		(0.01)
Location		2.684		2.214		2.108		2.164
		(1.88)*		(1.55)		(1.48)		(1.52)
Log # Analysts		-6.506		-6.991		-5.637		-6.164
		(1.15)		(1.23)		(1.00)		(1.09)
Log Size		9.346		1.018		1.013		1.066
		(2.45)**		(2.66)***		(2.65)***		(2.79)***
Log BM		2.205		2.364		1.455		1.850
		(2.49)**		(2.65)***		(1.61)		(2.06)**
Intercept	-0.294	-4.893	-0.294	-6.633	-0.294	-4.168	-0.294	-4.459
	(2.55)**	(1.64)	(2.55)**	(2.21)**	(2.55)**	(1.39)	(2.55)**	(1.48)
Adj. R^2	0.0024	0.0137	0.0011	0.0047	0.0051	0.0121	0.0044	0.0097
Industry F.E.	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Dependent Variable: CAR of Upgrades

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit Crisis	0.089	-1.850						
	(0.40)	(0.96)						
High Uncertainty			0.116	-2.336				
			(0.70)	(1.62)				
Recession Europe					0.139	-1.019		
					(0.84)	(0.70)		
Recession Finland							0.085	-3.124
							(0.56)	(2.31)**
LFR		-1.146		-1.114		-1.127		-1.070
		(2.17)**		(2.11)**		(2.13)**		(2.02)**
Location		2.588		2.497		2.567		2.454
		(1.77)*		(1.71)*		(1.76)*		(1.68)*
Log # Analysts		5.170		5.130		4.984		5.589
		(0.90)		(0.90)		(0.87)		(0.98)
Log Size		-5.270		-5.048		-5.176		-4.993
		(1.39)		(1.34)		(1.37)		(1.32)
Log BM		5.691		4.234		4.488		2.695
		(0.63)		(0.47)		(0.49)		(0.30)
Intercept	0.453	9.460	0.453	9.887	0.453	9.588	0.453	1.041
	(4.11)***	(3.20)***	(4.11)***	(3.33)***	(4.11)***	(3.20)***	(4.11)***	(3.49)***
Adj. R^2	0.0000	0.0014	0.0017	0.0020	0.0011	0.0014	0.0021	0.0027
Industry F.E.	No	Yes	No	Yes	No	Yes	No	Yes

Table 7 reports estimates of OLS panel regressions in which I control for firm, analyst, and recommendation characteristics to ensure the robustness of the results and that it is the bad times that drive the results. For all bad times measures and both upgrade and downgrades, I first estimate the CAR using a constant and a bad times indicator. The intercept is the CAR impact of good times and the coefficient on the bad times indicator is the additional impact of recommendation changes in bad times, which equal the CAR differences in Table 3. I cluster standard errors by calendar day to account for cross-sectional correlation of returns on the same day, following Loh and Stulz (2018).

For analyst and recommendation fixed-effects, I control for analyst influence and location. First, I use the analyst leader-follower ratio, *LFR*, which indicates a greater stock-price impact for leader analysts following Cooper, Day, and Lewis (2001). I calculate the LFR on a company basis for each analyst in the previous year by dividing the time from the previous recommendation with the time to the next recommendation and use the highest outstanding ratio for each analyst. A ratio over one indicates a leader analyst, since other analysts issue new recommendations more quickly after the leader's recommendation. Second, I use the location of the analyst's institution, as in local or foreign.

For firm fixed-effects, I control for the number of analysts covering each firm, *# Analysts,* as increases in the number of financial analysts improve information quality and efficiency of information distribution (e.g., Merkley, Michaely, Pacelli (2017)). Further, the number of analysts varies significantly over time, and is related to e.g., market returns, trading volume, and IPO activity, all of which are negatively affected in bad macroeconomic times. As other controls, I use firms' market capitalization from the previous year, *Size*, and book-to-market ratio *BM*, following Loh and Stultz (2018). I take logs for the firm fixed-effects to account for extreme values. Table 2 presents descriptive statistics on all of the control variables. In general, the characteristics look similar through good and bad times. Approximately, *CAR* and *LFR* increase and *# Analysts, Size,* and *MB* decrease in bad times.

I find weak evidence for bad times increasing the value of analyst output when including control variables for firm, analyst, and recommendation fixed-effects. In the downgrade sample, most of the coefficients on bad times measures are statistically insignificant. The exceptions are both measures in *Credit Crisis* and for *Recession Finland* when controlling for fixed-effects, which indicate that the bad times component does have a statistically significant effect on the price-impact during bad times. Thus, for downgrades, consistency with the findings of Loh and Stulz (2018) seems to appear in times of bad times in financial markets and during recession at the Finnish scope, consistent with analysts being better at analyzing the implications of local bad times.

For upgrades, I find similarly weak evidence for the value of analyst output increasing in bad times. Only the coefficient on *Recession Finland* when controlling for firm, analyst, and recommendation fixed effects. Thus, the effect of bad times is statistically significant for both upgrades and downgrades during *Recession Finland*, when controlling for fixed-effects. The intercepts for all time measures are all statistically significant at the 1%, indicating that other factors than what is included explain the results.

The results are mixed between the upgrade and downgrade samples for the control variables. For downgrades, market capitalization, *Size*, has a statistically significant effect for all bad times measures. Also, the book-to-market-ratio, *BM*, has a significant effect for all bad times measures expect *Recession Europe.* For upgrades, the analyst leader-follower-ratio, *LFR*, and *Location* of the analyst have significant effects for all bad times measures, implying that investors in Finland trust local and leader analysts for good news.

6. Conclusion

In this paper I assemble a data sample of analyst recommendations from 2006 to 2015 of OMX Helsinki companies to examine whether macro conditions affect the value of analyst output in Finland. I incorporate multiple proxies for bad macroeconomic times and use the price-impact following analyst recommendation changes as the indicator for value. Throughout the paper I assume that analyst behavior is fixed and the perceived value-effect occurs because of investors value analyst output differently.

I test four hypotheses and the results are as follows. First, I find weak evidence for analyst output being more valuable in bad times in Finland, inconsistent with the findings of Loh and Stulz (2018) in the US. Second, I find suspect evidence for local analysts being more informative than foreign peers. Third, I find weak evidence for a location-induced difference among analyst recommendations evening out as the scope of the bad times widens. Fourth, I am unable to credit increases in investors' reliance on analyst output for differences in analyst output value. Finally, using the CAPM as the return benchmark, I find strong evidence for analyst output being more valuable in bad times.

For future research, I would focus on examining why the effect of bad times on output value and for output in general is more pronounced in the US compared to Finland. First, I would examine whether analysts change their behavior in bad times. Second, I would study how various benchmarks models perform in both markets for the stocks that receive recommendations. Third, I would incorporate a more comprehensive model of investors' sources of information over economic times.

References

Bae, K., Stulz, R., Tan, H., 2008. Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts, *Journal of Financial Economics* 88, 581-606.

Barber, B., Lehavy, R., Trueman, B., 2007. Comparing the stock recommendation performance of investment banks and independent research firms, *Journal of Financial Economics* 85, 490-517.

Betrand, M. and Mullainathan, S., 2001. Do People Mean What They Say? Implications for Subjective Survey Data, *American Economic Review* 91, 67-72.

Bloom, N., 2009. The Impact of Uncertainty Shocks, *Journal of The Econometric Society* 77, 623-685.

Boni, L. and Womack, K., 2006. Analysts, Industries, and Price Momentum, *Journal of Financial and Quantitative Analysis* 41, 85-109.

Bradley, D., Clarke, J., Lee, S., Chayawat, O., 2014. Are analysts' recommendations informative? Intraday evidence on the impact of time stamp delays, *Journal of Finance* 69, 645-673.

Carhart, M., 1997. On persistence in mutual fund performance, *The Journal of Finance* 52, 57-82.

Chang, B., 2011. Investor Behavior and Economic Cycles: The Impact of Human Biases and Cognitive Limitations on Economic Booms and Busts, *The Journal of Behavioral Finance & Economics* 1, 1-26

Chinn, M. and Forbes, K., 2004. A Decomposition of Global Linkages in Financial Markets Over Time, *Review of Economics and Statistics* 86, 705-722.

Cooper, R., Day, T., Lewis, C., 2001. Following the leader: a study of individual analysts' earnings forecasts, *Journal of Financial Economics* 61, 383-416.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring Mutual Fund Performance with Characteristic-Based Benchmarks, *The Journal of Finance* 52, 1035-1058.

Frankel, R., Weber, J., 2006. Determinants of the Informativeness of Analyst Research, *Journal of Accounting and Economics* 41, 29-54.

Glode, V., 2011. Why Mutual Funds 'Underperform', *Journal of Financial Economics* 99, 546-559.

Haaparanta et al., 2017. 100 vuotta pientä avotaloutta – Suomen ulkomaankaupan kehitys, merkitys ja näkymät, Valtioneuvoston selvitys- ja tutkimustoimikunnan julkaisusarja 73, 158 p.

Hasbrouck, J., 1995. One Security, Many Markets: Determining the Contributions to Price Discovery, *The Journal of Finance* 50, 1175-1199.

Hirshleifer, D., Lim, S., Teoh, S., 2009. Driven to Distraction: Extraneous Events and Underreaction to Earnings News, *The Journal of Finance* 64, 2289-2325.

Hope, O. and Kang, T., 2005. The Association between Macroeconomic Uncertainty and Analysts' Forecast Accuracy, *Journal of International Accounting Research* 4, 23-38.

Kacperczyk, M., Seru, A., 2007. Fund Manager Use of Public Information: New Evidence on Managerial Skills, *The Journal of Finance* 62, 485-528.

Kacperczyk, M., Van Niewerburgh, S., Veldkamp, L., 2013. Time-Varying Fund Manager Skill, *The Journal of Finance* 69, 1455-1484.

Kretzmann, C., Maaz, C., Pucker, O., 2015. Sell side recommendations during booms and busts. *Risk governance & control: Financial markets & institutions* 5, 49-67.

Ljungqvist, A., Malloy, C., Marston, F., 2009. Rewriting History, *The Journal of Finance* 64, 1935-1960.

Loh, R. and Stulz, R., 2011. When Are Analyst Recommendation Changes Influential? *Review of Financial Studies* 24, 593-627.

Loh, R. and Stulz, R., 2018. Is Sell-Side Research More Valuable in Bad Times? *The Journal of Finance* 73, 959-1013.

Merkley, K., Michaely, R., Pacelli, J., 2017. Does the Scope of the Sell-Side Analyst Industry Matter? An Examination of Bias, Accuracy, and Information Content of Analyst Reports, *The Journal of Finance* 72, 1285-1334.

Michaely, R. and Womack, K., 1999. Conflict of Interest and the Credibility of Underwriter Analyst Recommendations, *The Review of Financial Studies* 12, 653-686.

Nyberg, P., Vaihekoski, M., 2014. Descriptive analysis of the Finnish stock market: Part II, Bank of Finland Research Discussion Papers 10, 34 p.

Pástor, L., Veronesi, P., 2009. Technological Revolutions and Stock Prices, *American Economic Review* 99, 1451-1483.

Schmalz, M., Zhuk, S., 2017. Revealing downturns, *Review of Financial Studies* (forthcoming).

Puttonen, V., 2004. ONKO OMISTAMISELLA VÄLIÄ?, www.eva.fi, Taloustieto Oy.

Womack, K., 1996. Do brokerage analysts' recommendations have investment value? *Journal of Finance* 51, 137-167.

Zhang, F., 2006. Information Uncertainty and Stock Returns, *The Journal of Finance* 61, 105-137.